Epidemic forecasts as a tool for public health: interpretation and (re)calibration

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Abstract

Objective: Recent studies have used Bayesian methods to predict timing of influenza epidemics many weeks in advance, but there is no documented evaluation of how such forecasts might support the day-to-day operations of public health staff.

Methods: During the 2015 influenza season in Melbourne, Australia, weekly forecasts were presented at Health Department surveillance unit meetings, where they were evaluated and updated in light of expert opinion to improve their accuracy and usefulness.

Results: Predictive capacity of the model was substantially limited by delays in reporting and processing arising from an unprecedented number of notifications, disproportionate to seasonal intensity. Adjustment of the predictive algorithm to account for these delays and increased reporting propensity improved both current situational awareness and forecasting accuracy.

Conclusions: Collaborative engagement with public health practitioners in model development improved understanding of the context and limitations of emerging surveillance data. Incorporation of these insights in a quantitative model resulted in more robust estimates of disease activity for public health use.

Implications for public health: In addition to predicting future disease trends, forecasting methods can quantify the impact of delays in data availability and variable reporting practice on the accuracy of current epidemic assessment. Such evidence supports investment in systems capacity.

Key words: influenza, epidemics, forecasting, public health

Influenza activity in temperate climates is markedly seasonal. However, epidemic characteristics such as timing and duration vary from year to year. This presents a substantial challenge to public health agencies and their capacity to identify and deliver proportionate responses (e.g. public health messaging, control measures, investigation efforts, surge capacity planning, staff rosters). In recent years, a number of studies have evaluated epidemic forecasting methods with a particular focus on seasonal influenza epidemics,[1–5] and we have previously demonstrated that seasonal influenza forecasts for the city of Melbourne (Australia) can be obtained using any one of several surveillance systems.[6] These methods could provide valuable support for public health preparedness and response, but a number of challenges remain to be addressed, including: "assessment of model calibration; integration of subjective expert input; operational research in pilot, real-world applications; and improved mutual understanding among modelers and public health officials".[1]

Our long-term aim is to establish a national influenza forecasting network in Australia by bringing together public health epidemiologists and modellers to evaluate and refine forecasting methods so that they can be integrated into routine infectious disease surveillance practice. Similar activities are being undertaken overseas, such as the Centers for Disease Control and Prevention's 'Epidemic Prediction Initiative'.[7] A critical factor in advancing these methods is to understand how epidemic forecasts are perceived and used by public health staff, and to tailor these tools to their needs.[8] Successful adoption requires forecasts to be reliable and accurate, and the expert knowledge of public health staff is an invaluable resource for meeting these criteria.[9] Successful adoption also requires public health staff to develop confidence in the forecasts, as obtained through first-hand experience.

This kind of predictive decision support tool offers the possibility of being able to make healthcare planning decisions (such as surging public health staff capacity and ensuring sufficient resources are available) with an understanding of what the future disease burden is likely to be, and how much

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(or how little) certainty we should place in these expectations. As seasonal influenza routinely places a massive burden on public healthcare systems,[10,11] tools that can help predict the timing and magnitude of this burden *in advance* are of real value to public health. This is of particular relevance in the event of a pandemic, because understanding the likely future impact of a pathogen is a fundamental aspect of our national pandemic response plans.[12,13]

The objective of this study was to report on a pilot real-world application of these forecasting methods, which involved public health staff from the Victorian Department of Health & Human Services (VDHHS) and the Victorian Infectious Diseases Reference Laboratory (VIDRL). Key observations from this study included challenges in interpreting incomplete surveillance data, the need for responsive adjustment of forecast calibration, and the value of incorporating expert opinion for improved forecast predictions.

Methods

Influenza notifications data

The notifiable diseases dataset includes only those cases that meet the Communicable Diseases Network Australia (CDNA) case definition for laboratory-confirmed influenza (one of: detection of virus by nucleic acid testing; isolation of virus by culture; detection of antigen by a validated antigen assay; seroconversion or a fourfold or greater rise in antibody titre to virus). In Victoria, medical practitioners and laboratories are required to notify the VDHHS of influenza cases that meet the CDNA case definition. The notifiable disease dataset represents only a small proportion of actual influenza cases in the community, since it includes only those cases where: a) the individual consults with a doctor; b) the doctor decides to collect a specimen for testing; c) the specimen collection is successful in isolating the virus; d) the lab test detects the virus; and e) the case is reported to the VDHHS. Reporting compliance is considered to be high for laboratories, but may not be perfect.[14]

Furthermore, only about half the notified cases are reported by medical practitioners and therefore *may* include an onset date (the date at which the patient reported the first occurrence of flu-like symptoms).[15] For the cases for whom only a laboratory notification is received, onset date is not available, therefore specimen collection date is used as a proxy. For the purposes of this study, the bias introduced by indexing notifications by onset date where available, and otherwise by the collection date, is assumed to be less than one week for the majority of cases, and is considered not to distort the data substantially.

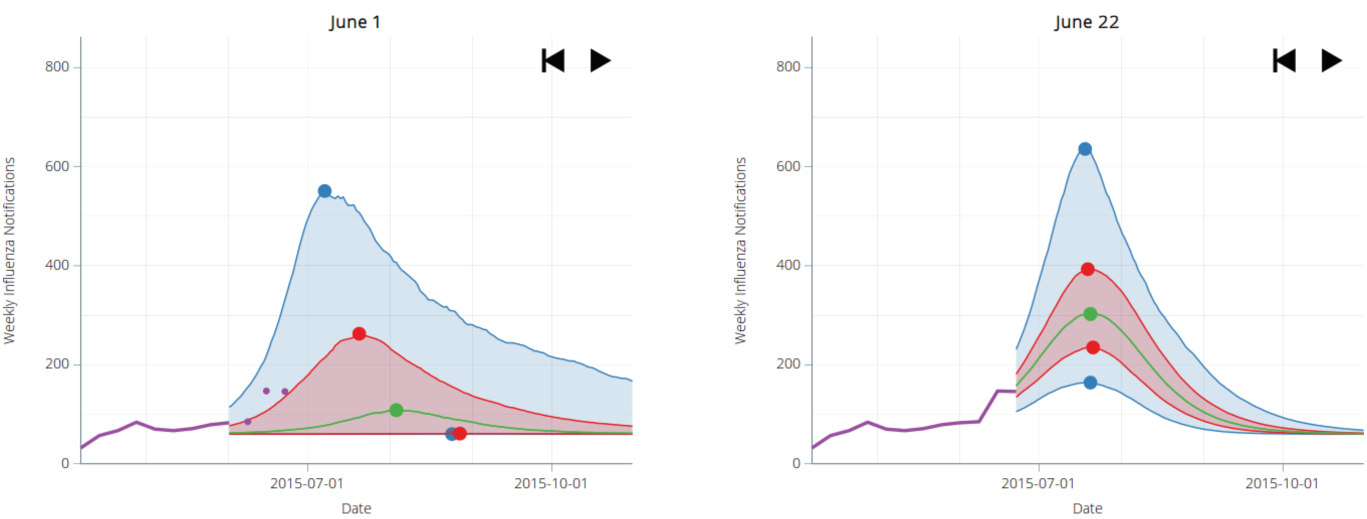
These data are available online from the VDHHS and are updated daily (https://www2.health.vic.gov.au/public-health/infectious-diseases/infectious-diseases-surveillance/infectious-diseases-surveillance-daily-summaries). Case notifications are sent to VDHHS by fax and by post, and are sorted by notification date (oldest first) before being manually entered into the data system. While weekly notification counts are reported on a timely basis in the summer months and during the early stages of each influenza epidemic, as the epidemic approaches peak incidence the data are subject to testing, reporting and data-entry delays, and so the count reported for a given week may not accurately reflect the true influenza burden in real time.

Communication of forecasting outputs

Forecasts were generated every Wednesday morning from April to November 2015 (inclusive) using weekly influenza notification counts as reported by the VDHHS for metropolitan Melbourne (comprising the 'Eastern', 'Northern and Western', and 'Southern' regions). Forecasts and the output visualisations took several minutes to produce, using a standard-issue laptop. We reported the median, 50% credible interval and 90% credible interval for the future weekly notification counts and for the timing of the epidemic peak.

Predictions of future incidence were made available online in the form of interactive animated plots (Figure 1) that allowed the user to explore how the forecasts evolved as data became available. Every week, the modellers emailed a summary and analysis

Figure 1: Online presentation of future incidence predictions, as generated on 24 June using data up to the week ending 22 June.



Data are shown in purple (solid lines indicate observations prior to the forecasting date, small dots indicate observations after the forecasting date). Median predictions are shown in green, 50% and 90% credible intervals in red and blue, respectively; filled circles indicate peaks, hovering the cursor over these circles displays the predicted date and notification count. The left panel shows the predictions when only using data up to 1 June, the right panel when using all available data (i.e., up to 22 June). The buttons in the top-right corner allow the user to step forward and backward in time to observe how the forecasts evolve.

of these outputs to VDHHS and VIDRL staff, seeking feedback on the predictions and the ways they were communicated. This weekly feedback helped improve the clarity and detail for the communication of the forecasting outputs, and we made minor refinements such as tool-tips that displayed numerical values when the mouse cursor hovered over credible interval peaks and weekly case notification counts. Each week we also evaluated how well the forecast predictions agreed with: a) the expert opinions of VDHHS and VIDRL staff; and b) syndromic surveillance data collected by the Victorian Sentinel Practice Influenza Network (VicSPIN).[16] The findings were subsequently reported at weekly VDHHS surveillance meetings. This feedback was also instrumental in guiding the recalibration process (described in the Results section).

Forecasting methods

We applied the forecasting method presented in our retrospective forecasting studies,[4,6] which combines an *SEIR* compartment model of infection with influenza notification counts through the use of a particle filter (see the Supplementary file for a complete description). As in our previous studies, we defined the relationship between disease incidence in the *SEIR* model and the weekly notification counts using a negative binomial distribution with dispersion parameter k.

The probability of being *observed* (i.e. of being reported as a notifiable case) was the product of two probabilities: that of becoming infectious (p_{inf}), and that of being identified (p_{id} – the likelihood of being symptomatic, presenting to a doctor, and having a specimen collected). The probability of becoming infectious was defined as the fraction of the *model* population that became infectious (i.e. transitioned from E to I), and subsumed symptomatic and asymptomatic infections.

Values for p_{id} and k were informed by retrospective forecasts using notifications data from previous seasons,[6] while the background notification rate p_{bg} was estimated from out-of-season notification levels in March and April 2015. We previously used this same method to estimate background notification rates for the 2010–14 seasons, which ranged from 15 to 46 cases per week,[6] but the estimated value was higher in 2015 (≈60 cases per week).

Results

Here we relate the forecast predictions and discussions between the modellers and the VDHHS and VIDRL staff, with respect to the influenza season. Figure 2 shows forecast predictions of observed incidence at every second week throughout the 2015 influenza season.

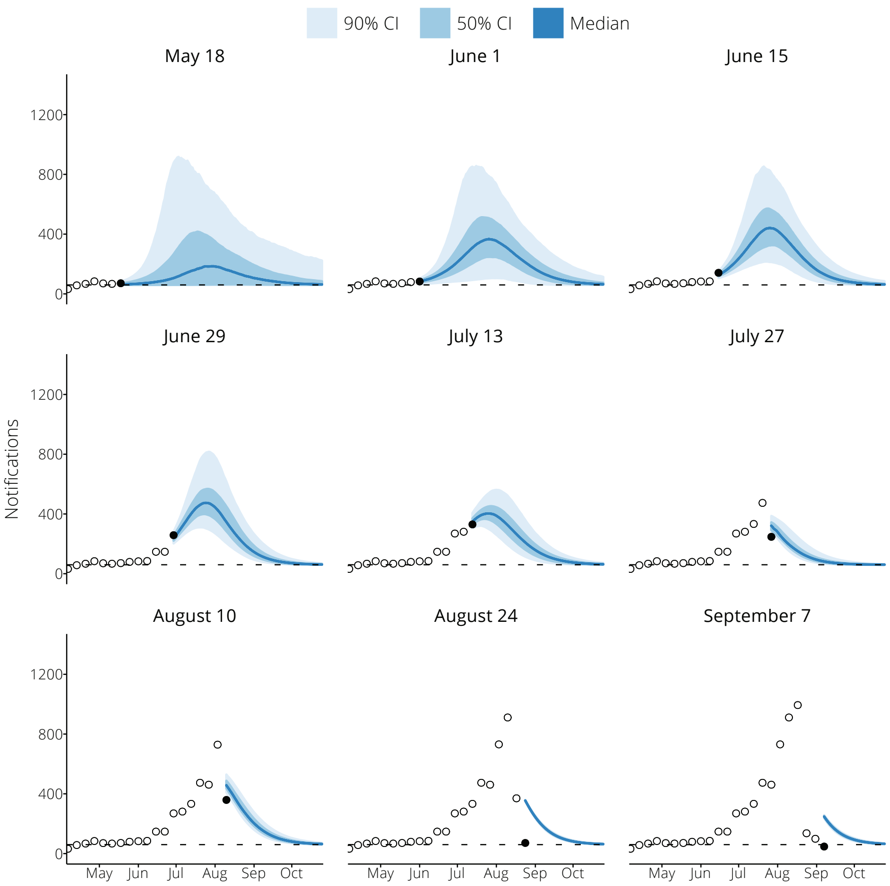
April and May

We began forecasting from the week ending on Sunday 5 April (2015), for which there were 32 notified cases. Subsequent weeks up to, and including, the week ending on 24 May would involve from 57 to 84 notified cases (mean of 70.7) and no evidence of growth over successive weeks. For this entire period, the 50% and 90% credible intervals for the future weekly notification counts included the background notification rate (i.e. the possibility that an epidemic would not occur). VDHHS staff reported that influenza type B was predominant at this early stage, which had not been observed since the 2008 influenza season,[17] and that influenza activity remained at pre-season level. This was consistent with forecast predictions, even though the weekly numbers of notified cases were higher than the assumed background level of 60 cases per week, so no adjustments were made to the forecast settings. There were also no clear expectations for the influenza season at this time.

June and July

In the first week of June, there was still no evidence of an influenza epidemic in the notifications data, despite media reports that the first five months of 2015 were the "worst on record".[18] The modellers subsequently asked whether the higher number of out-of-season influenza notified cases might be attributable, at least in part, to increased swabbing and testing; VDHHS staff advised that while this hypothesis could not be proven with complete certainty, it was quite likely. This suggested that the value p_{id}

Figure 2: Epidemic forecasts for the 2015 influenza season in metropolitan Melbourne, at nine dates during the first half of the season.



Weekly influenza case counts are shown as circles, and filled circles indicate the beginning of the forecasting period. Reporting and processing delays are evident in August, where counts are updated in subsequent weeks. The background notification rate is shown by the horizontal dashed line. Forecasts are shown as the median trajectory (solid blue line) and the 50% and 90% credible intervals around this trajectory (shaded regions).

might be higher than was estimated for the 2014 season but, in the absence of robust quantitative evidence, no adjustments were made to the forecast settings.

The week of 14 June, with 147 influenza cases, was the first occasion where more than 85 notified cases were reported. With this first evidence of seasonal influenza activity, the epidemic peak was predicted to occur in the second half of July, which was consistent with VDHHS staff expectations at that time. By 28 June, the peak timing predictions had remained stable for three weeks and predicted the peak would occur between 19 July and 29 July. These predictions were still stable by 12 July (i.e. for five weeks); in retrospective forecasts of previous years, this typically indicated that the forecasts were accurate.[6] These predictions also remained consistent with VDHHS expert opinion, although all participants were cautious and did not place complete confidence in the predictions.

Influenza type A and type B were observed to be co-circulating with around 50–60% of sub-typed samples being Influenza type B, and appeared to be growing synchronously. The modellers asked whether it might be expected for one type to overtake the other and give rise to a second peak/shoulder later in the year. Advice from VDHHS staff was that, as observed in previous years, type A might start to overtake type B later in the season and become predominant for the remainder of the season.

August onward

There were near-identical notification counts for the weeks ending 19 July and 26 July, and substantially fewer notified cases for the week ending 2 August; forecast predictions remained consistent with those obtained over the past six weeks, indicating that the peak may have indeed occurred as predicted.

However, in the first week of August, VDHHS staff experienced an unprecedented backlog of approximately 1,000 case notifications. This indicated that the case counts for the previous two weeks would increase substantially and VDHHS staff advised that the seasonal peak had probably not yet passed. VicSPIN syndromic surveillance data also indicated that the peak had not yet passed. Evaluating the forecasts under these real-world conditions of delayed reporting and data entry were clear concerns for all participants. Such circumstances are the greatest challenge for epidemic forecasts and are also the situations in which robust forecasts are of greatest value.

As of the week ending 16 August, the week of 9 August was seen to be the peak week with 859 notified cases, and VDHHS staff reported that notifications for past weeks were still arriving from laboratories. In comparison, the highest peak observed in previous seasonal influenza epidemics was only 560 notified cases. By this point it had become clear that our forecast settings – based on retrospective forecasts of the 2010–14 influenza seasons using the same data source[6] – were not consistent with the 2015 data, and we immediately explored adjustments to these settings (see next section).

For the rest of August, notification counts for all weeks of August continued to increase and the data eventually comprised five sequential weeks with more than 1,000 notified cases each, an entirely unprecedented rate of notifications that did not reflect an unusually large influenza burden. Other syndromic and hospital-based surveillance systems indicated that the 2015 season was not appreciably more severe than the 2014 season, and the final Australian Influenza Surveillance Report for 2015 reported "clinical severity appeared less than last year".[19]

Forecast adjustment

Evidence from other surveillance systems indicated that the increase in notified cases was more likely a result of increased testing than of increased incidence. In terms of the forecast settings, this meant that the observation probability (p_{id}) was too low. Using the most recent data snapshot (as of week ending 16 August) we tested retrospective forecasts with increased values for (p_{id}), generated for each week in June and July. An appropriate range for these increased values was based on the rate at which notifications were being received by VDHHS (i.e. prior to those notifications appearing in the data extracts). These forecasts were in best agreement with the observed data for August when (p_{id}) was increased from 0.0025 to 0.012. This represents a five-fold increase in the combined probability of infected individuals: a) being symptomatic; b) presenting to a doctor; and c) having a specimen collected.

During the six-week peak period there were 7,043 notified cases; if this indeed represents 1.2% of the 'true' incidence, then just under 600,000 people would have been infected in those 6 weeks – 14% of the Melbourne population (4.1 million). The same reasoning for previous seasons suggests that the 'true' incidence in the peak six weeks was 32% in 2014 (3,662 cases, $p_{id} = 0.0025$) and 23% in 2013 (2,004 cases, $p_{id} = 0.002$). However, in our model simulations we assume that the entire population is susceptible to infection, meaning that disease incidence in these simulations is substantially higher than expected in the actual population.

With this updated setting, the peak timing was accurately predicted 10 weeks in advance and these predictions remained stable as the peak was approached, only deviating from the true peak when the reporting and processing delays became substantial in the last week of July (see Figure 3, top row). This shows that forecasts can be recalibrated on a near-real-time basis, making use of expert opinion and available data as a guide.

We noted in June that the approximate 20% increase in out-of-season cases (compared to 2014) might indicate an increase in testing and that p_{id} should have been increased. However, the relationship between out-of-season cases and in-season testing was unclear and this change was substantially smaller than the five-fold increase in p_{id} described here, so it is not a reliable indicator of changes in testing practices.

Notification delays

The effect of reporting and processing delays on the weekly notification counts is shown in Figure 4. Significant delays only became evident when the (eventual) weekly counts approached that of the 2014 peak (560 notified cases, which itself was the highest number of cases since the 2009 H1N1 pandemic). Prior to 2015, delays of one week or more were only observed in mid-2009 during the H1N1 pandemic, when laboratory tests were recommended for all patients presenting with influenza-like illness. Previous seasonal influenza epidemics in this setting have seen delays of no more than a few days, rendering 2015 a particularly unusual influenza season. Importantly, the delays experienced in 2015 were the result of backlogs in laboratory testing and in VDHHS data entry. Laboratory delays were evident in weeks for which notifications data entry had been completed, but which subsequently experienced a further increase in cases. Even with an automated online notification system in place, there would have been delays of up to several weeks.

Having reached the end of the 2015 Melbourne influenza season, we generated retrospective forecasts that used the same settings and the final notification counts for each week to evaluate the impact of these delays on the forecasting predictions.

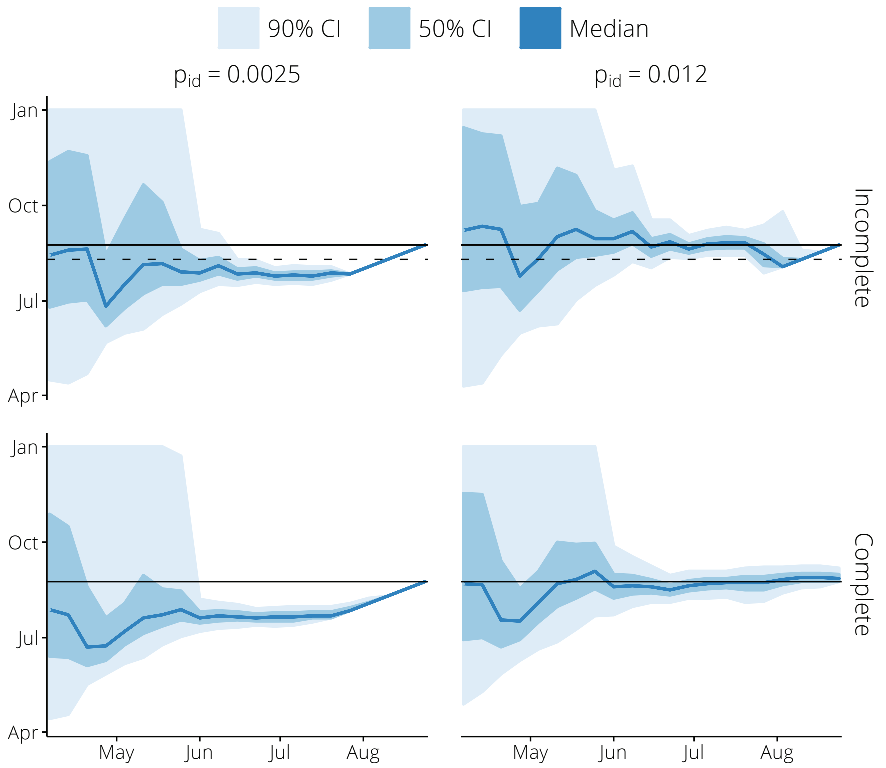
Despite using the complete counts for each week, the forecasts obtained with the original settings (p_{id}=0.0025) were not substantially better (Figure 3, bottom left). However, as shown in Figure 5, when p_{id} was increased to 0.012 the predicted notification counts were in much better agreement with the August data from as early as mid-June (compare the 15 June forecasts in Figures 2 and 5). With this updated setting, the peak timing was accurately predicted many weeks in advance, and these predictions remained stable right up to the peak (Figure 3, bottom right).

Season summary

The peak of the 2015 Melbourne influenza season occurred in week 35 (the week ending 30 August) with more than 1,300 cases notified for the week; more than 7,000 cases were notified in the six-week period between weeks 32–37. This represented an unprecedented number of notifications for influenza over what was otherwise largely considered to be a moderate season in terms of severity. The median age of cases was 36 years, with 46% of cases occurring in the 20–60-years age groups. Cases in the younger age groups (0–4 years and 5–9 years) represented 19% of the total number of cases. Cases aged 60 years and over represented 23% of the case total. Although the season is described as being one in which type A and B influenza were co-circulating, it became overwhelmingly dominated by type B as the season progressed.

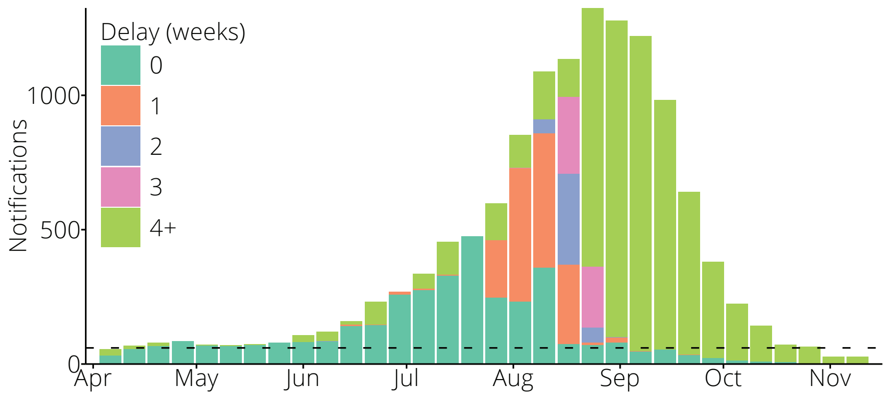
The Influenza Complications Alert Network (FluCAN) is a sentinel hospital-based surveillance program that records hospitalisations with laboratory-confirmed influenza, which involves one regional and three metropolitan participating sites in Victoria. The peak in Victorian FluCAN influenza hospitalisations occurred in week 35 (the same week as the peak in influenza case notifications, see Figure S1 in the Supplementary file) and the distribution of type A and B influenza hospitalisations (47% A, 53% B) was similar to that observed in the notifications data (41% A, 59% B).[20] The authors also reported that while previous studies have noted "a lower clinical severity of illness associated with influenza B […] we found that the proportion of patients requiring intensive care admission was similar for those with influenza B compared with influenza A".

Figure 3: The predicted peak timing (y-axis) plotted against the forecasting date (x-axis); the observed peak in the live (incomplete) data is indicated by the dashed horizontal line, the true peak (observed in the complete data) is indicated by the solid horizontal line.



When using the live (incomplete) data the peak timing was predicted several weeks too early (top left). These predictions were greatly improved when the observation probability (p_{id}) was increased from 0.0025 to 0.012, until August when marked delays immediately preceding peak incidence greatly affected the data (top right). With the complete data (bottom row), the predictions did not improve with p_{id} = 0.0025 (bottom left) but were greatly improved with p_{id} = 0.012 (bottom right) and remained accurate and stable right up to the peak.

Figure 4: The reporting and processing delays throughout the 2015 season. The dashed horizontal line indicates the background notification rate.



Discussion

Principal findings

In this collaboration, we conducted a pilot study of epidemic forecasting for public health decision support, coinciding with a marked increase in influenza testing and unprecedented numbers of notified cases, in the absence of other health sector indicators of a concomitant increase in disease activity. These unique circumstances presented a challenge to public health staff in their regular duties and in the provision of expert opinion to inform the forecasts. They also presented a major challenge to forecast calibration, but we were nevertheless able to recalibrate the forecasts two weeks prior to the true epidemic peak (the week ending 30 August) and obtain accurate forecasts.

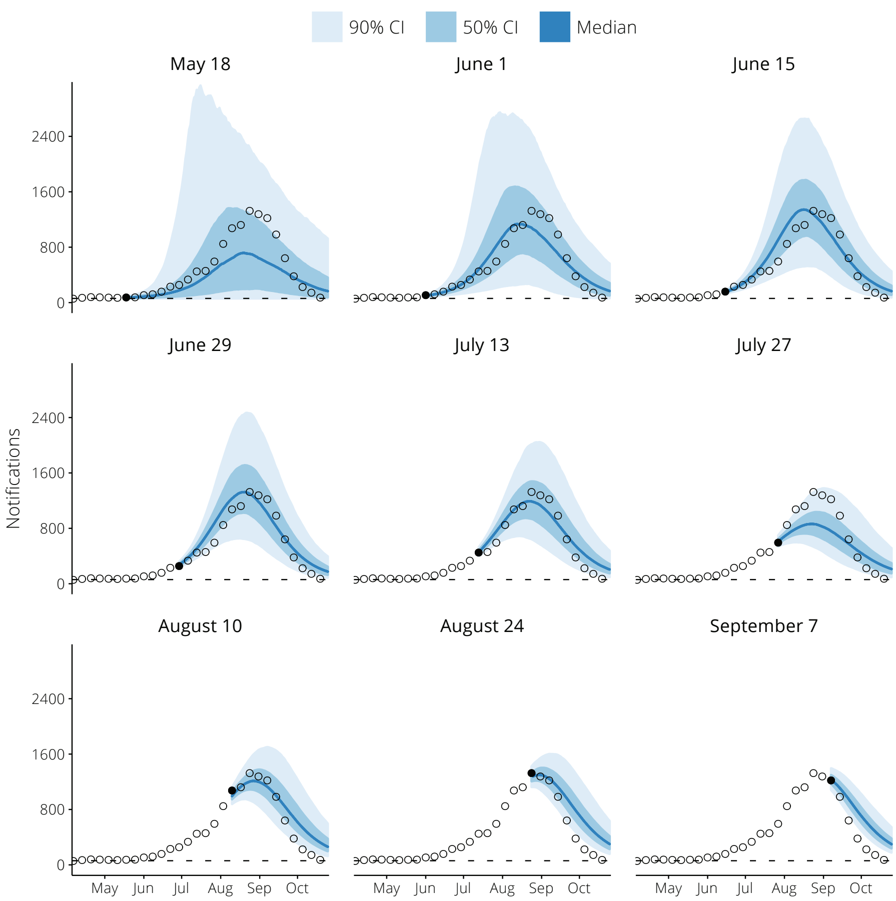
We also measured the impact that delayed reporting of surveillance data has on forecast performance, which has clear implications for future surveillance investment efforts. Timely case reporting is of particular concern for live forecast evaluation, because features (e.g. the epidemic peak) may only become evident in retrospect and, more importantly, it can greatly complicate forecast (re)calibration. More immediately, these methods must be extended to appropriately handle data backlogs in future influenza seasons.

We also observed that the interpretation and communication of the forecasting outputs developed appreciably over the year. This demonstrates the value of pilot studies for developing familiarity with, and critical insights into, epidemic forecasts as a tool for public health.

Study strengths and weaknesses

Epidemiological forecasting presents a fundamental challenge in that disease surveillance systems are inherently affected by human behaviours, which hugely complicates the calibration of these methods (unlike, say, radar detection of moving objects). The increase in confirmed influenza cases in 2015 in Melbourne, Australia, while unprecedented in magnitude, reflects a long-term trend evident in national notifications data, where increased testing has caused annual case notifications to increase substantially,[21] despite the lack of concomitant increases in burden (as assessed by other syndromic and hospital reporting systems) in these years.[19,20,22] The importance of reporting both positive and negative test results has been recognised in Australia for a number of years,[23] on the grounds that this would greatly improve our understanding of influenza burden both in-season and out-of-season.[24] Thus, in order to provide accurate forecasts in future influenza seasons, it is critical to characterise changes in surveillance relative to previous influenza seasons,[6] as influenced by human and social factors (such as healthcare-seeking and testing behaviours).

Figure 5: Epidemic forecasts for the 2015 influenza season in metropolitan Melbourne in the absence of reporting and processing delays, when the observation probability was increased from 0.0025 to 0.012, representing a near-five-fold increase in ascertainment.



In most influenza seasons, there are multiple circulating types and/or subtypes and it might appear preferable to use a multi-strain infection model, but this presents some serious challenges. It is not obvious how to accurately model the co-circulation of competing (sub)types,[25,26] particularly in light of recent studies that indicate cross-protective immune responses are hierarchical.[27,28] However, if the circulating (sub)types are similarly transmissible, overall influenza activity may still be characterised by a single-strain model, as used in this study. Note that this allows knowledge of the circulating (sub)types and their risk profiles to provide an *additional layer of interpretation about the consequences of infection*. For example, since almost 60% of the influenza case notifications in 2015 were for influenza B, we would have expected young children to represent a greater-than-normal proportion of the notified cases (and influenza hospitalisations) in future weeks. Similar extrapolations from the projected influenza activity could also be made depending on whether A(H1N1) or A(H3N2) is the dominant strain, with A(H3N2) being generally understood to result in a greater proportion of cases that require hospitalisation. The use of case notification forecasts to predict other indicators of influenza severity and/or burden was not explored in this pilot study, but is a logical extension that would provide valuable input for guiding public health resource allocation activities.

Our use of a single-strain model did not compromise the forecasts and, by virtue of having fewer model parameters than a multi-strain model, it requires fewer observations to inform the model parameters. This study also provided a valuable opportunity for near-real-time evaluation and discussion of forecasting outputs and surveillance data between mathematical modelers and epidemiologists for the duration of the influenza season. Perhaps the most illuminating conversations occurred when forecast credible intervals were broad (i.e. uncertain) and the surveillance data was inconclusive, and we sought a common ground of informed uncertainty ('known unknowns') upon which to base our intuition.

Comparison to other studies

The aim of our study was to understand how forecasts are used and evaluated by public health staff. A number of studies have evaluated influenza forecasting techniques in France,[29] Singapore,[30] the US[31] and Hong Kong,[32] and other studies have tested alternate data streams.[33,34] But none of these studies have examined forecasts from a perspective of integrating forecasts into public health practice.

These studies were not subject to substantial variations in reporting behaviours from year to year, and common findings include the ability to accurately predict epidemics several weeks in advance. As we have shown here and previously,[6] when the forecasts are calibrated appropriately we obtain similarly accurate predictions (Figure 5).

Meaning and implications

The challenge of interpreting surveillance data with characteristics that vary from year to year has been discussed in the context of Australian pertussis notifications,[35] but has not been raised in the existing influenza forecasting literature. However, it is of broader relevance, because surveillance data is influenced by public perception of risk and by public health messaging, and these factors will change markedly in the event of a pandemic or the emergence of a novel pathogen, in any setting. It is important to note that using the percentage of influenza-positive tests, rather than the number of notified cases, is not a panacea since it is also influenced by healthcare-seeking and testing behaviours. This is a global challenge for infectious disease forecasting, and it reinforces the importance of understanding "the processes that determine how persons are identified by surveillance systems in order to appropriately adjust for the biases that may be present".[36] Forecast calibration might also be enhanced by incorporating additional data streams, including novel sources that can assess human behaviour, but this presents a number of novel challenges.[37]

Another key challenge is relating the predicted influenza activity (as characterised here by case notifications data) to severity and/or burden measures, such as influenza hospitalisations, so that the forecasts are of greater relevance to public health activities. Estimation of the true burden of influenza from existing surveillance systems is challenging, given their ability to accurate identify only a small proportion of cases presenting to clinical services, which themselves are only a small subset of those in the community. While not the focus of the present work, Bayesian modelling approaches that synthesise multiple sources of evidence, related to those underpinning our predictive algorithm, show promise for improving assessment of population exposure and severity assessment.[38]

By deploying forecasts as a matter of routine in future influenza seasons, building on the lessons learned in this study, we aim to augment existing VDHHS efforts to, for example, alert healthcare workers and institutions to possible increases in cases, proactively adapt surge capacity plans, and inform staff rostering for case follow-up, investigation efforts, and data entry. This collaboration is ongoing as of the 2017 influenza season, and public health staff in other Australian jurisdictions are now participating. Our long-term aim is to integrate these tools into routine public health practice at a national level.

Ethics committee approval

Access to the 2015 influenza case notifications data for metropolitan Melbourne was approved by the Health Sciences Human Ethics Sub-Committee, Office for Research Ethics and Integrity, The University of Melbourne (Application ID 1544262.1).

References

1. Chretien J-P, George D, Shaman J, Chitale RA, McKenzie FE. Influenza forecasting in human populations: A scoping review. *PLoS One*. 2014;9(4):e94130.
2. Nsoesie EO, Brownstein JS, Ramakrishnan N, Marathe MV. A systematic review of studies on forecasting the dynamics of influenza outbreaks. *Influenza Other Respir Viruses*. 2014;8(3):309–16.
3. Yang W, Karspeck A, Shaman J. Comparison of filtering methods for the modeling and retrospective forecasting of influenza epidemics. *PLoS Comput Biol*. 2014;10(4):e1003583.
4. Moss R, Zarebski A, Dawson P, McCaw JM. Forecasting influenza outbreak dynamics in Melbourne from Internet search query surveillance data. *Influenza Other Respir Viruses*. 2016;10(4):314–23.
5. Zarebski AE, Dawson P, McCaw JM, Moss R. Model selection for seasonal influenza forecasting. *Infect Dis Model*. 2017;2(1):56–70.
6. Moss R, Zarebski A, Dawson P, McCaw JM. Retrospective forecasting of the 2010–14 Melbourne influenza seasons using multiple surveillance systems. *Epidemiol Infect*. 2017;145(1):156–69.
7. Biggerstaff M, Alper D, Dredze M, Fox S, Fung IC-H, Hickmann KS, et al. Results from the Centers for Disease Control and Prevention predict the 2013–2014 influenza season challenge. *BMC Infect Dis*. 2016;16(1):357.
8. Muscatello DJ, Chughtai AA, Heywood A, Gardner LM, Heslop DJ, MacIntyre CR. Translation of real-time infectious disease modeling into routine public health practice. *Emerg Infect Dis*. 2017;23(5).
9. Farrow DC, Brooks LC, Hyun S, Tibshirani RJ, Burke DS, Rosenfeld R. A human judgment approach to epidemiological forecasting. *PLoS Comput Biol*. 2017;13(3):e1005248.
10. Muscatello DJ, Amin J, MacIntyre CR, Newall AT, Rawlinson WD, Sintchenko V, et al. Inaccurate ascertainment of morbidity and mortality due to influenza in administrative databases: A population-based record linkage study. *PLoS One*. 2014;9(5):e98446.
11. Schanzer DL, Schwartz B. Impact of seasonal and pandemic influenza on emergency department visits, 2003–2010, Ontario, Canada. *Acad Emerg Med*. 2013;20(4):388–97.
12. Department of Health. *Australian Health Management Plan for Pandemic Influenza*. Canberra (AUST): Government of Australia; 2014.
13. Moss R, McCaw JM, Cheng AC, Hurt AC, McVernon J. Reducing disease burden in an influenza pandemic by targeted delivery of neuraminidase inhibitors: Mathematical models in the Australian context. *BMC Infect Dis*. 2016;16(1):552.
14. Dalton CB, Carlson SJ, Butler MT, Elvidge E, Durrheim DN. Building influenza surveillance pyramids in near real time, Australia. *Emerg Infect Dis*. 2013;19(11):1863–5.
15. Rowe SL. Infectious diseases notification trends and practices in Victoria, 2011. *Vic Infect Dis Bull*. 2012;15(3):92–7.
16. Kelly H, Murphy A, Leong W, Leydon J, Tresise P, Gerrard M, et al. Laboratory-supported influenza surveillance in Victorian sentinel general practices. *Commun Dis Intell*. 2000;24(12):379–83.
17. NNDSS Annual Report Writing Group. Annual report of the National Notifiable Diseases Surveillance System, 2008. *Commun Dis Intell Q Rep*. 2010;34(1):8–22.
18. Butt C. Flu cases tracking at record levels. *Sydney Morning Herald*. 2015; Jun 5.
19. Department of Health. *Australian Influenza Surveillance Report: 26 September to 09 October 2015*. Canberra (AUST): Government of Australia; 2015.
20. Cheng AC, Holmes M, Dwyer DE, Irving LB, Korman TM, Senanayake S, et al. Influenza epidemiology in patients admitted to sentinel Australian hospitals in 2015: The Influenza Complications Alert Network. **Commun Dis Intell.** 2016;40(4):e521–6.
21. NNDSS Annual Report Writing Group. Australia's notifiable disease status, 2011: Annual report of the National Notifiable Diseases Surveillance System. *Commun Dis Intell Q Rep*. 2013;37(4):e313–93.
22. Fielding JE, Regan AK, Dalton CB, Chilver MB-N, Sullivan SG. How severe was the 2015 influenza season in Australia? *Med J Aust*. 2016;204(2):60–1.
23. Lambert SB, Faux CE, Grant KA, Williams SH, Bletchly C, Catton MG, et al. Influenza surveillance in Australia: We need to do more than count. *Med J Aust*. 2010;193(1):43–5.
24. Kelly HA, Grant KA, Tay EL, Franklin L, Hurt AC. The significance of increased influenza notifications during spring and summer of 2010-11 in Australia. *Influenza Other Respir Viruses*. 2012;7(6):1136–41.
25. Recker M, Blyuss KB, Simmons CP, Hien TT, Wills B, Farrar J, et al. Immunological serotype interactions and their effect on the epidemiological pattern of dengue. *Proc R Soc*. 2009;276(1667):2541–8.
26. Truscott J, Fraser C, Cauchemez S, Meeyai A, Hinsley W, Donnelly CA, et al. Essential epidemiological mechanisms underpinning the transmission dynamics of seasonal influenza. *J R Soc Interface*. 2011;9(67): 304–12.
27. Laurie KL, Guarnaccia TA, Carolan LA, Yan AWC, Aban M, Petrie S, et al. Interval between infections and viral hierarchy are determinants of viral interference following influenza virus infection in a ferret model. *J Infect Dis*. 2015;212(11):1701–10.

28. Cao P, Yan AWC, Heffernan JM, Petrie S, Moss RG, Carolan LA, et al. Innate immunity and the inter-exposure interval determine the dynamics of secondary influenza virus infection and explain observed viral hierarchies. *PLoS Comput Biol*. 2015;11(8):e1004334.
29. Viboud C, Boëlle P, Carrat F, Valleron A, Flahault A. Prediction of the spread of influenza epidemics by the method of analogues. *Am J Epidemiol*. 2003;158(10):996–1006.
30. Ong JBS, Chen MI-C, Cook AR, Lee HC, Lee VJ, Lin RTP, et al. Real-time epidemic monitoring and forecasting of H1N1-2009 using influenza-like illness from general practice and family doctor clinics in Singapore. *PLoS One*. 2010;5(4):e10036.
31. Shaman J, Karspeck A, Yang W, Tamerius J, Lipsitch M. Real-time influenza forecasts during the 2012-2013 season. *Nat Commun*. 2013;4:2837.
32. Yang W, Cowling BJ, Lau EHY, Shaman J. Forecasting influenza epidemics in Hong Kong. *PLoS Comput Biol*. 2015;11(7):e1004383.
33. Hickmann KS, Fairchild G, Priedhorsky R, Generous N, Hyman JM, Deshpande A, et al. Forecasting the 2013–2014 influenza season using Wikipedia. *PLoS Comput Biol*. 2015;11(5):e1004239.
34. Santillana M, Nguyen AT, Dredze M, Paul MJ, Nsoesie EO, Brownstein JS. Combining search, social media, and traditional data sources to improve influenza surveillance. *PLoS Comp Biol*. 2015;11(10):e1004513.
35. Kaczmarek MC, Valenti L, Kelly HA, Ware RS, Britt HC, Lambert SB. Sevenfold rise in likelihood of pertussis test requests in a stable set of Australian general practice encounters, 2000–2011. *Med J Aust*. 2013;198(11):624–8.
36. Reed C, Chaves SS, Daily Kirley P, Emerson R, Aragon D, Hancock EB, et al. Estimating influenza disease burden from population-based surveillance data in the United States. *PLoS One*. 2015;10(3):e0118369.
37. Althouse BM, Scarpino SV, Meyers LA, Ayers JW, Bargsten M, Baumbach J, et al. Enhancing disease surveillance with novel data streams: Challenges and opportunities. *EPJ Data Sci*. 2015;4:17.
38. Presanis AM, Pebody RG, Paterson BJ, Tom BDM, Birrell PJ, Charlett A, et al. Changes in severity of 2009 pandemic A/H1N1 influenza in England: A Bayesian evidence synthesis. *BMJ*. 2011;343:d5408.

Supporting Information

Additional supporting information may be found in the online version of this article:

Supplementary File: Forecasting methods.